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Baseline Classification of Acoustical Signatures of Mine-Like Objects

Jüri Sildam

John A. Fawcett

Defence R&D Canada – Atlantic

Technical Memorandum

DRDC Atlantic TM 2005-058

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Canada

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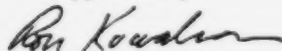
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Abstract

We investigate the problem of the detection of mines and the sensitivity of a binary classifier to mine types using a broadband signal incident upon an elastic object. In the course of the sensitivity analysis a realistic situation is simulated when a binary classifier that is optimal for a part of collected- or modeled data turns out to be sub optimal for new, previously unseen data. In general, such a problem corresponds to a generalization problem when for the purpose of classification analysis, the data is set is divided into three parts: training data, test data used for classifiers' fine tuning via cross-validation, and test data not used in the cross-validation. However, in addition to such division, we ensure that one or more types of mines' acoustical signatures are left out of training data, as well as out of test data used for cross-validation purposes. We call such approach a Baseline Classification. To create a data set of mine-like and non mine-like objects that includes the required diversity of mine types, we use analytical models for the elastic shelled spheres and for infinite elastic shelled cylinders. We use a total of 9600 spectra. The spectra can be divided according to their shape, shell material, filling, relative thickness, and surrounding environment into eight types of mines and non-mines. Boundary between mines and non-mines is defined by the relative thickness of shells and it is found that a threshold of 3.5% is optimal. The shells thinner or equal than 3.5% were defined as mines, whereas the rest of shells were defined as non-mines. Overall classification error rate varied from 8 to 23%. As expected, classification accuracy changed significantly with respect to the classes of objects in training set, indicating the cases when the classifier could fail.

Résumé

Les caractéristiques temporelles (ou de fréquence ou de temps-fréquence) du signal rétrodiffusé sont examinées lors de l'analyse de classification de signaux sonar large bande. Nous espérons que la réponse structurelle-élastique produite par les mines sera sensiblement différente de celle produite par les objets naturels, comme les roches. Le cas échéant, cette réponse fournirait des renseignements utiles permettant de distinguer les mines du clutter. Une telle approche peut être considérée comme complémentaire à l'analyse d'image acoustique spatiale normalement utilisée avec un sonar haute fréquence bande étroite à balayage latéral.

Nous avons analysé une situation relativement commune où l'on a une connaissance très générale des différents types de mines, mais pas une connaissance détaillée sur leur signature acoustique large bande respective. Dans une telle situation, il ne serait guère surprenant qu'un système de classification formé à l'aide d'un ensemble limité de signatures acoustiques ne soit pas à la hauteur face à un nouveau type de mine. Nous avons analysé le problème de détection/classification des mines en utilisant un signal large bande. En particulier, nous avons examiné la sensibilité du processus de classification par rapport aux types de mines inclus dans l'ensemble d'apprentissage.

Pour obtenir un ensemble de données sur les objets qui ressemblent à des mines et ceux qui ne leur ressemblent pas, qui tient compte de la diversité requise quant aux types de mines, nous avons utilisé des modèles analytiques de sphères à coquille élastique et de cylindres infinis à coquille élastique. Nous avons utilisé un total de 9 600 spectres. Ces spectres peuvent être classifiés en huit types de mines et d'objets autres que des mines, selon leur forme, le matériau de leur coquille, leur contenu, leur épaisseur relative et selon leur milieu. La frontière qui sépare les mines des objets qui n'en sont pas est définie par l'épaisseur relative des coquilles. Il semble que le seuil optimal aux fins de classification est de 3,5 %. Les objets dont l'épaisseur de la coquille est plus mince ou égale à 3,5 % ont été définis comme étant des mines, alors que les autres ont été définis comme ne l'étant pas. La précision globale de classification variait de 77 à 92 %. Nous avons conclu que le fait de ne pas inclure certains types de mines dans l'ensemble d'apprentissage a entraîné l' " échec " du système de classification.

Executive summary

INTRODUCTION

Minehunting is the main method to conduct mine countermeasures operations and reducing false alarms is the key factor for the success of a minehunting sonar. In particular, for classification purposes, manmade shelled objects should be distinguishable from natural mine-sized clutter. The characteristics of the echo from a broadband signal incident upon an object may yield valuable classification information with respect to the structure of the object. We generate from models the wideband backscattered spectra for many different types of spheres and cylinders with different surrounding environments. We investigate the sensitivity of the classification accuracy to the shell thicknesses, the shell materials, and the surrounding environments included in the training set. Results of this investigation are related to the practical scenario of using a trained classifier in the field when an unknown target type or new environmental condition is encountered.

RESULTS

We show that in general, a Kernel Machine classifier provides robust and accurate results for distinguishing thin-shelled from manmade objects. The optimal thickness threshold for differentiating between shelled and solid objects is a shell thickness of about 3.5% of its radius. A classification accuracy of 92% was obtained when a random selection of all object types were used in training. In the case that an entire class of the objects was not included in the training set, the classification accuracy varied significantly with respect to this class.

SIGNIFICANCE OF RESULTS

The results of this report extend beyond the classification issues of mine detection. The results of the sensitivity analysis can be generalized to a number of classification problems such as ASW, diver detection etc. For the mine detection problem, a straightforward classifier which yielded robust, accurate classification results was presented.

FUTURE WORK

It is hoped that we can test the classifier of this report, trained with model data, with actual experimental backscattered data. In particular, using the presented sensitivity analysis, it would be interesting to investigate if it is possible to use a combination of simple shapes to train a classifier that will classify correctly an object with a different and possibly more complicated shape. Diver detection is another problem where it would be interesting to apply the classification approach presented in this report.

Sildam J., Fawcett J., Baseline Classification of Acoustical Signatures of Mine-Like Objects, DRDC Atlantic TM 2005-58, Defence R& D Canada-Atlantic

Sommaire

SOMMAIRE

La chasse aux mines est la principale méthode utilisée pour mener des opérations de lutte contre les mines. De plus, la diminution du nombre de fausses alarmes est le facteur clé qui détermine le succès du sonar de chasse aux mines. En particulier, aux fins de classification, on devrait pouvoir distinguer entre les objets à coquille faits par l'homme et le clutter naturel de la taille d'une mine. Les caractéristiques de l'écho d'un signal large bande incident sur un objet peuvent fournir des données sur sa structure, qui sont précieuses aux fins de classification. Nous avons utilisé des modèles pour générer le spectre rétrodiffusé large bande de nombreux types différents de sphères et de cylindres dans différents milieux. Nous avons analysé la sensibilité de la précision de classification en fonction de l'épaisseur des coquilles, des matériaux des coquilles et des milieux, compris dans l'ensemble d'apprentissage. Nous avons fait le lien entre les résultats de la présente analyse et un scénario pratique dans lequel un classificateur formé est utilisé sur le terrain lorsqu'un type inconnu de cible ou une condition environnementale nouvelle surgissent.

RÉSULTATS

Nous avons démontré que, de façon générale, un système de classification à noyau (Kernel Machine) fournit des résultats robustes et précis pour la distinction entre les objets à coquille mince et les objets faits par l'homme. Le seuil optimal d'épaisseur pour distinguer entre les objets à coquille et les objets solides est une épaisseur de coquille d'environ 3,5 % du rayon de l'objet. Une précision de classification de 92 % a été obtenue en utilisant, pendant l'apprentissage, une sélection aléatoire parmi tous les types d'objets. Cependant, lorsqu'une classe entière d'objets n'était pas incluse dans l'ensemble d'apprentissage, la précision de classification variait de façon significative par rapport à la classe en question.

PORTÉE

Les résultats décrits dans le présent rapport vont au-delà des questions de classification relatives à la détection de mines. En effet, les résultats de l'analyse de sensibilité peuvent être généralisés par rapport à un certain nombre de problèmes de classification liés, par exemple, à la lutte anti-sous-marine ou à la détection de plongeurs. Pour ce qui est du problème de détection de mines, nous avons présenté un système de classification simple qui donne des résultats robustes et précis.

RECHERCHES FUTURES

Nous espérons pouvoir tester le système de classification, proposé dans le

présent rapport, formé à l'aide de données modélisées avec des données expérimentales de rétrodiffusion. En particulier, il serait intéressant d'étudier, en utilisant l'analyse de sensibilité présentée, la possibilité d'établir une combinaison de formes simples pour former un système de classification qui va classer correctement un objet ayant une forme différente et, probablement, plus complexe. Il serait aussi intéressant d'appliquer l'approche de classification présentée dans le présent rapport au problème de détection de plongeurs.

Sildam J., Fawcett J., Baseline Classification of Acoustical Signatures of Mine-Like Objects (Classification de base des signatures acoustiques des objets semblables aux mines), RDDC Atlantique TM 2005-58, R & D pour la défense Canada - Atlantique.

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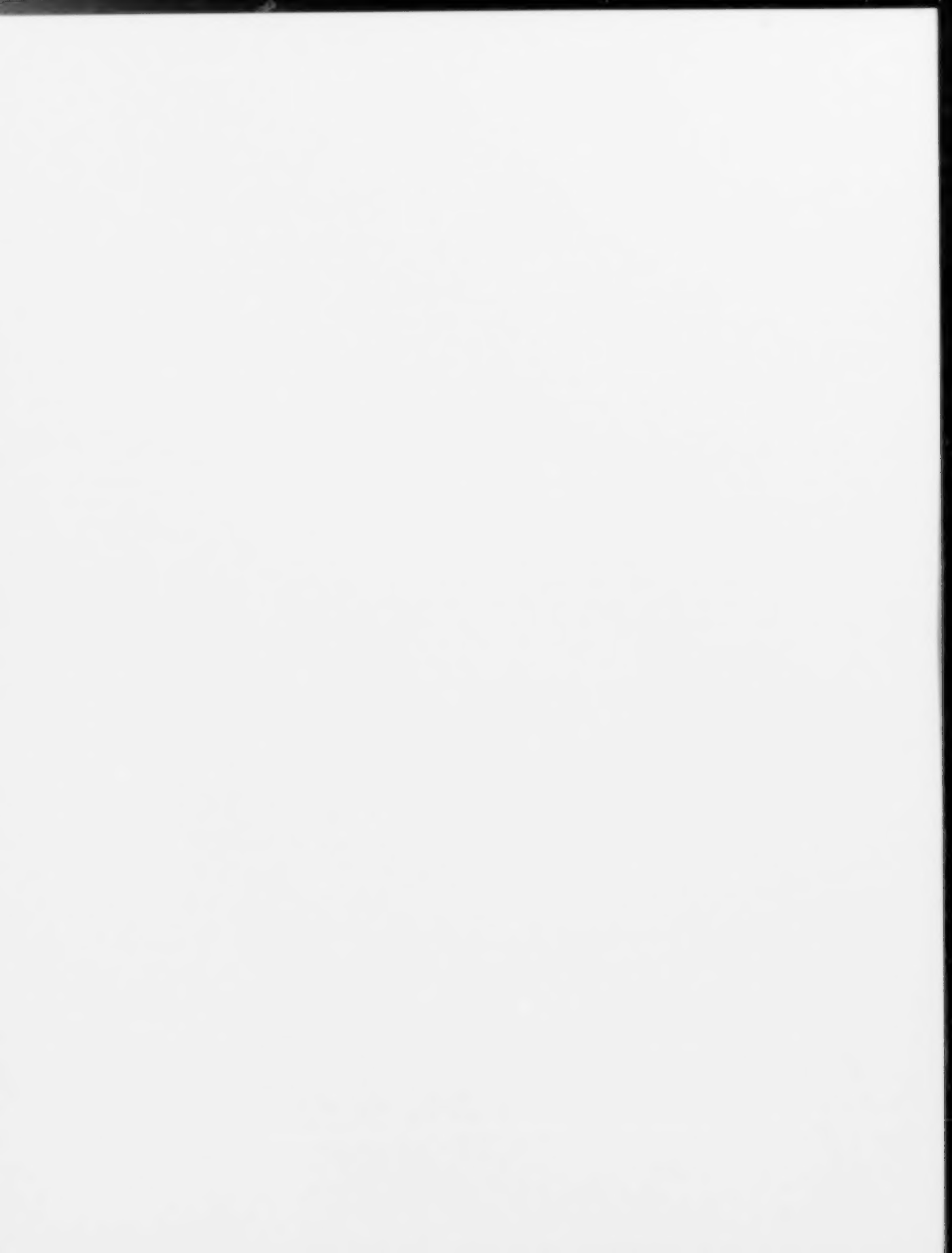
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1 Introduction

A high frequency sidescan sonar can be used to build up an image of the seafloor. This image is constructed from the amplitude of the envelope of the backscattered signal for a relatively narrowband pulse at a high frequency (for example, at 455 kHz for the Klein 5500 sonar). In this case, the classification of objects on the seabed is based upon the estimated length and height of the object and possibly on some image statistics. In general, this approach is based upon the spatial characteristics of the sonar returns, and it is sometimes difficult to differentiate between a mine and a non-mine that have similar dimensions.

Another approach to sonar signal classification is to instead use a wideband sonar signal (i.e., its frequency bandwidth is a significant fraction of the centre frequency) and consider the temporal (or frequency or time-frequency) characteristics of the backscattered signal. It is hoped that the elastic-structural response of manmade mines is significantly different than natural occurring objects such as rocks. This is the approach we will emphasize in this paper - the classification of a single sonar time series, which results from the scattering of a wideband sonar signal. We are concerned with the classification of a scatterer as a mine or a non-mine. However, it is anticipated that the approach of this paper also has applications for the classification of ASW sonar signals and also for the classification of echoes which might result in a Harbour Protection system.

The classification performance that can be achieved for a sonar system will depend significantly on the sonar parameters. For example, which range of frequencies yields the best discriminatory information? How large a bandwidth is required so that a variety of sizes of objects can be classified? A modeling approach can provide a cost effective means to address such questions. The classification performance will depend also on the choice of the classifier and on its optimization. Another important factor, which we stress in this report, is the robustness of the classifier performance to the classes of targets and conditions included in the training set. For example, is a classifier which is not trained with respect to a certain type of object able to successfully classify it as minelike?

2 On Generalization of Classification Analysis

In supervised pattern analysis, classification is carried out in two steps. An existing data set is divided into two parts: training and test data. The training data is used to train a classifier, and the test data is used to test the trained classifier with new previously unseen data. A classifier is said to generalize well if it classifies correctly the new, unseen test data. It is hoped then that a trained classifier will also correctly classify the data that is collected at some future time (for example, during a trial). The division into the training and the test data can be carried out just once (e.g. using 50% of data for training and another 50% for testing) or repeatedly so that the content of the training and test data are changed many times. For example "leave one out" (l.o.o.) cross-validation uses all but one data vector for training, and the one vector that has been left out of the training set is used for testing. By repeating l.o.o. N times, where N equals to a number of data vectors of the existing data-set, statistically significant estimates of the classifiers generalization ability are achieved. The training set can be subdivided into a training and a crossvalidation set. The crossvalidation set is used to "tune" the classifier's parameters for optimal performance. This optimised classifier can then be applied to the test data.

3 Generalization of Classification of Acoustical Signatures

The question of a classifier's ability to generalize well when new target types have been encountered can be addressed using statistical models, physical models, experimental data, or finally using some combination of experimental data and models. In the present work, we use the physical-analytical models for an elastic shelled sphere (with or without interior fill) and for an infinite elastic shelled cylinder (at broadside aspect). The advantage of using modeling is that we can quickly generate the backscattered spectra for thousands of objects (different radii, different thickness, different shell materials, and even surrounding sediment). These objects can be grouped according to their type (i.e. according to shape, shell material, interior fill, and surrounding sediment). By leaving any of these types out of the training data one can test how a classifier can handle new previously unseen types of targets. This is in contrast to a prevailing classification approach where the training and the test data are simply chosen randomly.

The effect of different incident pulse types can be very quickly examined by appropriately weighting the computed complex spectra. In what follows we will emphasize the relative shell thickness of an object as the discriminator between mine-like or non mine-like. We will examine how accurately we can estimate this parameter for a wide variety of elastic spheres and cylinders and then finally we will examine the resulting classification performance of the classifier as a function of the thickness threshold defined for differentiating between mine-like or non mine-like objects.

4 Baseline Classification

An approach that we call Baseline Classification of mines can be seen as a series of classification tests aimed at the estimation of a chosen classifier's sensitivity to the mine types included in the training. A schematic, shown in Figure 1 demonstrates this concept. For simplicity, we assume that each measurement of an acoustic signal consists of only two features. The measurements have to be divided into two classes: mines and non-mines. We generate four clouds of artificial data points. Let us assume also that the markers of blue color correspond to mines and that the red markers correspond to non mines. The solid straight line that separates these two classes corresponds to a plane found as the solution of linear ridge regression problem. Panel A shows the situation where there is one distinct class of mines and one class of non-mines used for training. Panel B shows the same situation as shown in panel A with different classes of mines and non-mines used for training. Panel C shows what happens if panel A measurements are used for the classifier training, and panel B measurements are used for the classifier testing. Finally, panel D shows an opposite case that of panel C (i.e. when data shown on panel B was used for training, and data shown on panel A was used for testing). One can see that while in the former case (panel C) test data classification results remain very good, in the latter case (panel D) the classifier fails. The present case demonstrates that the shown classifier is very sensitive to the change of the given mine type used in the training set. Such a sensitivity analysis can be used to decide what kind of improvements are required to train a robust classifier, and the impact of the choice of mine shapes needed to train a robust classifier. For example one may ask, if a classifier was trained using spherical and cylindrical mines, could it classify a mine with some other shape? Additionally, one may ask, could one use a classifier trained with only model data for the accurate classification of field measurements?

5 On Choice of a Classification Algorithm

One of the fundamental problems of a classification analysis of data with an unknown probability distribution is a lack of the knowledge about whether the classification results are optimal. In other words, in the case of analysis of data collected in field, it is not possible, as a rule, to tell whether a better classifier can be found as compared to the currently chosen one. A good example of such uncertainty is the discrimination analysis of cylinder-shaped rocks versus hollow cylinders in the data set presented by Gorman and Sejnowski [1]. This

data set has been used as a benchmark data-set for numerous studies ([2] [3] [4] [5] [6]). Different linear and non-linear classifiers have been tested on this data set with a varying success. Recently, it was found that the two classes in this data set were, in fact linearly separable [7].

Generally the results of any classification analysis depend on a combination of three factors: the type of data, the choice of classifier, and the fine-tuning of the classifier of choice. For example, a classifier that seems to be the best choice for one data set can perform less successfully on another data set. An example of another experiment, relevant to the present paper, was carried out by Zakharia and Chevret [8]. These authors used backscattering measurements from spheres and cylinders with hemispherical end-caps of different sizes, materials, and thicknesses, in their investigation of discriminating between shells (mines) and solid targets (mine-like objects). Using a neural network trained on randomly selected backscattered data (measured at different angles), and tested on the rest of data, they achieved a classification accuracy as high as 94%. The results of these various experiments imply that one can expect that the results of mine detection can vary from good to excellent. What remains unclear is how sensitive a trained classifier would be if a new, previously unseen mine type was encountered. How diverse should the training data set be in terms of different mine types to minimize classifier's sensitivity and to improve its robustness? The present work is a first step in addressing this question.

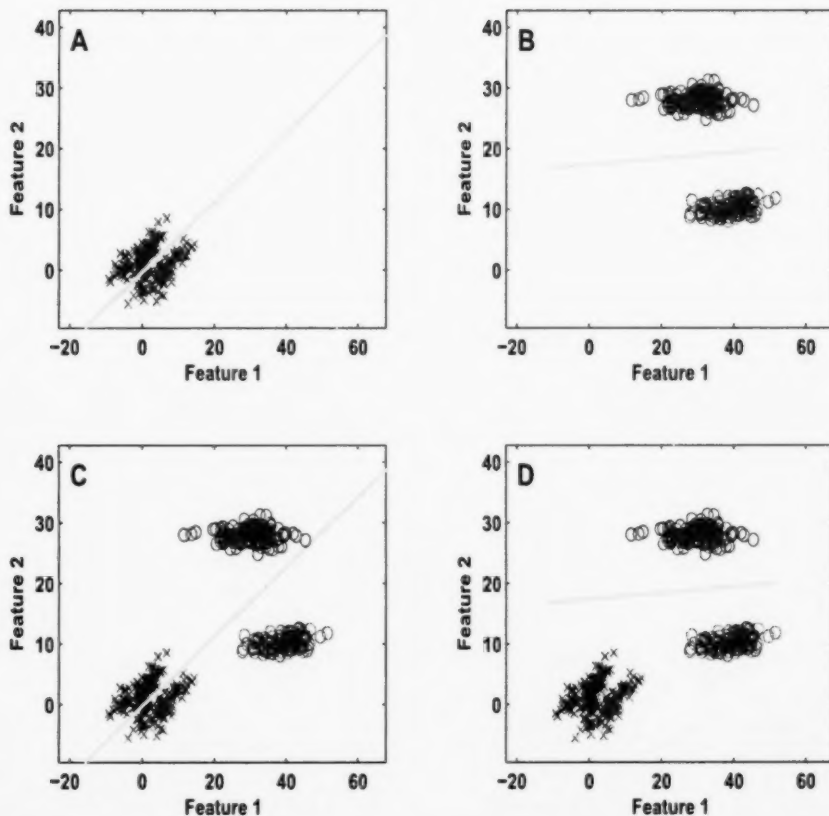


Figure 1: Cartoon demonstrating the idea of Baseline Classification; Using the data of one mine type for training, and the data of another mine type for testing, one gets an idea about the sensitivity of a classifier to the change of a particular mine type; see text for details

6 Notation

$s(\omega)$ - complex spectrum of analytical model output
 $w(\omega)$ - complex spectrum of a Gaussian waveform
 ω - frequency, $\omega = \{50, 100, 150, \dots, 100000\}$ Hz
 $\mathbf{x} = |\mathbf{s} \cdot \mathbf{w}| / \|\mathbf{s} \cdot \mathbf{w}\|^2$ - input spectrum
 y - a label of $\mathbf{x}$. In a case of regression analysis $y = \log(h/a)$ is a logtransformed relative thickness of a shell, in a case of binary classification, $y = \pm 1$;
 h - shell thickness
 a - shell outer radius
 l - number of training samples
 $n = 2000$ - dimension of input space
 $\mathbf{S}_{\text{train}} = \{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_l, y_l)\}$ - training set
 $\mathbf{K}_{\text{train}} = \langle \phi(\mathbf{x}_i), \phi(\mathbf{x}_j) \rangle; i = 1, \dots, l; j = 1, \dots, l$ training kernel matrix
 $\mathbf{K}_{\text{test}} = \langle \phi(\mathbf{x}), \phi(\mathbf{x}_j) \rangle; j = 1, \dots, l$ test kernel matrix for a spectrum $\mathbf{x}$
 $\mathbf{K}_{\text{train}} = \exp(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}); i = 1, \dots, l; j = 1, \dots, l$ training kernel matrix calculated using RBF
 $\mathbf{K}_{\text{test}} = \exp(-\frac{\|\mathbf{x} - \mathbf{x}_j\|^2}{2\sigma^2}); j = 1, \dots, l$ test kernel matrix calculated using RBF for a spectrum $\mathbf{x}$
 $\mathbf{I}$ - identity matrix
 $\lambda > 0$ - constant
 ϕ - embedding map
 $\Phi = \phi(\mathbf{x}_i), i = 1, \dots, l$
 $g(\mathbf{x})$ - prediction function
 $\mathbf{w} = w_1, w_2, \dots, w_l$ - weight vector
 $\langle \mathbf{x}_i, \mathbf{x}_j \rangle$ - inner product of two input vectors

7 Problem Formulation

Given a labeled training data set $S = \{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_l, y_l)\}$ where $\mathbf{x}_i = (x_1, \dots, x_n)$ is a n dimensional normalized wide-band spectrum, and y_i is a label associated with this spectrum, the aim of the classification analysis is to find a real-valued linear function $g(\mathbf{x}_i)$ that will predict the corresponding labels with a minimal statistical error. In a case of binary classification of mines, the spectra that correspond to mines are labeled as $y_i = -1$ and the spectra of non-mines are labeled as $y_i = +1$. In a case of regression analysis, the input spectra $\mathbf{x}_i$ are associated with the relative thicknesses $y_i = \log(h_i/a_i)$. Given a threshold y_{th} , the results of the regression analysis can be used to predict whether the input spectra belong to thin shells (mines) or to thick shells (non-mines).

In this report, the classification analysis is based on the minimization of the quadratic loss function L

$$\min_{\mathbf{w}} L = \min_{\mathbf{w}} \lambda \|\mathbf{w}\|^2 + \sum_{i=1}^l (y_i - g(\mathbf{x}))^2 \quad (1)$$

where λ is a positive number that controls the degree of regularization. Depending on the problem formulation, Eq. 1 corresponds either to a classical ridge regression (RR) or to a kernel ridge regression (KRR) problem. It can be shown that in the case of RR, the weight vector $\mathbf{w}$ is derived in the form:

$$\mathbf{w} = (\mathbf{X}'\mathbf{X} + \lambda \mathbf{I}_n)^{-1} \mathbf{X}'\mathbf{y} \quad (2)$$

where $\mathbf{X}$ is a data matrix with the normalized input wide-band spectra stored as row vectors.

For the KRR problem, $\mathbf{w}$ is calculated as:

$$\mathbf{w} = \Phi(\Phi'\Phi + \lambda \mathbf{I}_n)^{-1} \mathbf{y} \quad (3)$$

where Φ is a data matrix with the input wide-band spectra mapped into a high-dimensional feature space. Note that in practice a non-linear map Φ is not calculated explicitly. Rather, a so called kernel trick (discussed below) is used.

To predict a label of a test input $\mathbf{x}$ one has to calculate:

$$g(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x} \rangle \quad (4)$$

where $\langle \mathbf{x}_1, \mathbf{x}_2 \rangle$ denotes the inner product. For the RR problem, Eq.(2), the numerical complexity of this task is $O(n^3)$. For the KRR problem, Eq.(3), the explicit mapping of input data into higher dimensional would be computationally prohibitive. Instead of calculating $\mathbf{w}$ explicitly (which gives so called primal solution), one rewrites Eq. (2) as a linear combination of the training points and obtains $\mathbf{w} = \mathbf{X}' \boldsymbol{\alpha}$ (for details see e.g. [9]), where $\boldsymbol{\alpha} = (K + \lambda \mathbf{I}_l)^{-1} \mathbf{y}$. Now, the complexity of computing $\boldsymbol{\alpha}$ is equal to $O(l^3 + l^2 n)$, and Eq. 4 can be rewritten as:

$$g(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x} \rangle = \mathbf{y}' (\mathbf{K}_{\text{train}} + \lambda \mathbf{I}_l)^{-1} \mathbf{K}_{\text{test}}. \quad (5)$$

The complexity of evaluating g on a new example is $O(ln)$. In a linear case $\mathbf{K}_{\text{train}} = \mathbf{X}_{\text{train}} \mathbf{X}_{\text{train}}'$ and $\mathbf{K}_{\text{test}} = \mathbf{X}_{\text{test}} \mathbf{X}_{\text{train}}'$. In a non-linear case, $\mathbf{K}_{\text{train}} = \langle \phi(\mathbf{x}_i), \phi(\mathbf{x}_j) \rangle, i = 1, \dots, l; j = 1, \dots, l$, and $\mathbf{K}_{\text{test}} = \langle \phi(\mathbf{x}_i), \phi(\mathbf{x}) \rangle, i = 1, \dots, l$. One can see that the kernel matrices are formulated in terms of inner products of either the input vectors (linear case) or in terms of the inner products of maps of input vectors (non-linear case). In the latter case, the explicit calculation of $\phi(\mathbf{x})$ can be avoided by constructing a kernel matrix with the help of an appropriate (i.e. that meets Mercer's conditions [10]) kernel function. The choice of a kernel function is not a trivial problem. Fortunately, in many practical cases, frequently used kernel functions such a polynomial (Eq. 6) or radial basis function (Eq. 7) give excellent classification results,

$$K(\mathbf{x}_i, \mathbf{x}_j) = (\langle \mathbf{x}_i, \mathbf{x}_j \rangle + c)^p \quad (6)$$

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}\right). \quad (7)$$

The results of the KRR analysis presented in the next section will be based on

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|}{2\sigma^2}\right). \quad (8)$$

8 Results

In this section we first consider two classification problems found in the literature. The same approach is then used for the classification of elastic-shelled objects. The feature vector we use for the following examples is simply the spectral amplitudes of the signal, which is used as an input into a linear ridge regression or into a non-linear kernel ridge-regression classifier.

The goal of the first experiment we consider is to discriminate between two artificially generated chirps. Davy et. al. [11] [12] have used this model as a benchmark for testing various classifiers and various optimization approaches.

$$\text{Class1} : \mathbf{x}(t) = \sin[2\pi(f_0 t + \psi_0)] + \sin[2\pi(s_1^1 t^2 + f_1 t + \psi_1)] + \varepsilon(t)$$

$$\text{Class2} : \mathbf{x}(t) = \sin[2\pi(f_0 t + \psi_0)] + \sin[2\pi(s_1^2 t^2 + f_1 t + \psi_1)] + \varepsilon(t)$$

where ψ_0 and ψ_1 are uncorrelated random initial phases, randomly distributed in $[0; 1]$, $f_0 = 0.25$ and $f_1 = 0.4$ are fixed normalized frequencies, and $\varepsilon(t)$ is Gaussian white noise of variance $\sigma_\varepsilon^2 = 2$. The chirp slopes s_1^1 and s_1^2 are randomly and uniformly distributed in the frequency ranges of $[0.10; 0.20]$ and $[0.25; 0.35]$ respectively (Fig. 2, the upper panels). Prior to classification, the time series of Class 1 and Class 2 were Fourier transformed. The absolute values of the respective spectra were used as input $\mathbf{x}$ to the RR and KRR classifiers. The whole data set consists of 20000 spectra. One hundred spectra were used for training and the rest, 19900, were used for testing. The error rates for the test data were 4% and less than 2% for the RR and KRR methods respectively. Ridge regression classification results are shown in the lower panels of Fig. 2. The predicted labels of the chirps of the class $y = -1$, are usually negative (Fig. 2, the left panels), and the predicted labels of the chirps of the class $y = +1$ are usually positive (Fig. 2, the right panels). The positive predicted labels for the class $y = -1$ would result in a classification error (and similarly for negative label values for class $y = +1$).

The goal of the second experiment was to apply the RR and KRR classifiers on a real-world data-set [1] used as benchmark by a number of researchers (see section 5 of the present work). This data set consisted of 208 spectra obtained from backscattering measurements of cylinder shaped rocks and steel cylinders. To compare this with the finding of the linear separability reported in ([7]), a RR was first trained using the whole dataset. The resulting training data classification error was 9% (see Figure 3). Next, the classifiers were retrained and tested using a l.o.o. cross-validation approach. In this case the test data errors were 26% and 14% for the RR and KRR classifiers respectively.

In the third experiment, we generated 9600 spectral signatures of targets using analytic models for spherical and infinite cylindrical shells (broad side aspect). The analytical models for the elastic-shelled spheres and elastic-shelled infinite cylinders are based on the spherical harmonic and cylindrical Bessel function expansions of all field quantities. The expansion coefficients of the special functions are then determined by satisfying the appropriate boundary conditions at interfaces (see, for example, [13], [14], [15]).

We grouped all spectra into 96 subgroups, where each subgroup consisted of 100 spectra (because of computer memory problems and computation speed, for final classification, we used only every second spectra i.e. 50 out of 100), which varied according to shell thickness (see Table 1). As the next step these subgroups were used to form eight groups. Each group included the acoustical signatures of one mine type (here we use terms "type" and "class" interchangeably). Below is the list of these eight mine types organized pair wise:

- spherical and cylindrical shells
- shells, filled with water and shells, filled with air
- shells, made out steel and shells, made out of other materials (see Table 1)
- shells, placed into water and shells, placed into sand

Altogether we carried out 10 classification subexperiments¹. Input into the KRR classifier was calculated as follows:

$$\mathbf{x}(\omega) = \frac{|\mathbf{s}(\omega) \cdot \mathbf{w}(\omega)|}{\|\mathbf{s} \cdot \mathbf{w}\|^2} \quad (9)$$

where $\mathbf{s}(\omega)$ denotes the Fourier transform of the time series of the model output, and $\mathbf{w}(\omega)$ is Fourier transform of incident signal (see Fig. 4).

During the first experiment, the data subdivision into the training and test sets was carried out randomly, so that 94% of data was included into the training set, and remaining 6% of data was included into the test set. Each input vector was labeled using a log-transformed relative thickness of a shell (i.e. $y_i = \log(h_i/a_i)$ where h is the thickness and a is the outer radius of the sphere or cylinder). To obtain statistically significant results, regression analysis was repeated 96 times, each time randomly changing the training and test data. This experiment was also used to fine tune the KRR. The results of the regression analysis are shown in Figure 5. The right middle panel shows

¹the term *subexperiments* refers here to the classification experiments conducted as a part of the third experiment. For simplicity the term *sub* is dropped in the following text

a ROC curve that was obtained by using the relative thickness as a threshold to divide the targets into two classes; this threshold was gradually changed to create the curve. The classification error is shown separately for thin and thick targets as a function of the log-transformed threshold in the upper right panel of Figure 5. It can be seen that classification error was relatively low for target thicknesses in the range 1-10%. The optimal thickness was 3.5%.

For the remaining 9 experiments, the classifier structure was kept constant i.e. we used only the kernel given by Equation (8) with $\sigma = 1$. Note that during the 10th classification experiment (similar to the first experiment), the training and the test data were chosen randomly. The results of the binary classification, using 3.5% as the threshold dividing the training set into the mines and non-mines, are presented in Table 2 and in figures 6-13. The ROC curves of the test data are generated by varying the threshold of the prediction function $g(\mathbf{x})$ value. The accuracies are quoted for the threshold of zero. In the Experiment 7, a low 47% classification accuracy was obtained. However, the ROC curve of Fig. 13 indicates that using an optimal class-label threshold (different from zero) leads to a 88% accuracy. Unfortunately, in practice, this optimal threshold value would not be known apriori. Note also that the classification results of the Experiments 7 and 3 are asymmetrical relative to their pair-wise counterparts (Table 2). For example, when the KRR classifier was trained, using acoustic signatures of all air-filled shells, and tested on all types of water-filled shells, the classification accuracy was 83%. In the opposite case, when the KRR classifier was trained using acoustical signatures of all water-filled shells and tested on all air-filled shells, the classification results were indistinguishable from a random guess. In fact, in the case of the Experiments 3 and 7, the classification results could have been almost 100% wrong (see Table 2 and Figures 9 and 13, where the blue line shows the classification results and the green line shows true label values) if the test data included only mines (i.e. thin shells). This classification bias and the observed asymmetric classification results can be explained by the situation shown in Fig. 1. For example, in the case of satisfactory classification results, the hyperplane in feature space that correctly divides the air-filled shells into two classes, also accurately divides the water-filled shells into mines and non-mines. In the opposite case, however, the hyperplane in feature space that divides the water-filled shells into two classes, leaves all the air-filled shells on one side of this hyperplane.

Shape	Filling	Material	Surrounding Environment	Size $a(m)$	Relative Thickness y
Sphere Cylinder	Water Air	Steel Aluminium Limestone Basalt	Water Sand	0.125-0.5	0.1-93% distributed logarithmically

Table 1: Characteristics of the shells used for classification

No	Experiment name	Train Data Type	Train (%)	Test Data Type	Test (%)	Accuracy (%)
1	Regression	Random	94	Random	6	92
2	Filling 1	Air	67	Water	33	83
3	Filling 2	Water	33	Air	67	47
4	Material 1	Steel	25	Other	75	87
5	Material 2	Other	75	Steel	25	85
6	Environment 1	Water	67	Sand	33	85
7	Environment 2	Sand	33	Water	67	47
8	Shape 1	Sphere	50	Cylinder	50	77
9	Shape 2	Cylinder	50	Sphere	50	77
10	Random Data	Random	75	Random	25	87

Table 2: An overview of the classification experiments; Columns "Train" and "Test" indicate the data type that has been used for training or testing; Columns "Train %" and "Test %" show the percent of data that has been used for training or testing; Column "Accuracy" shows the overall classification accuracy in percent

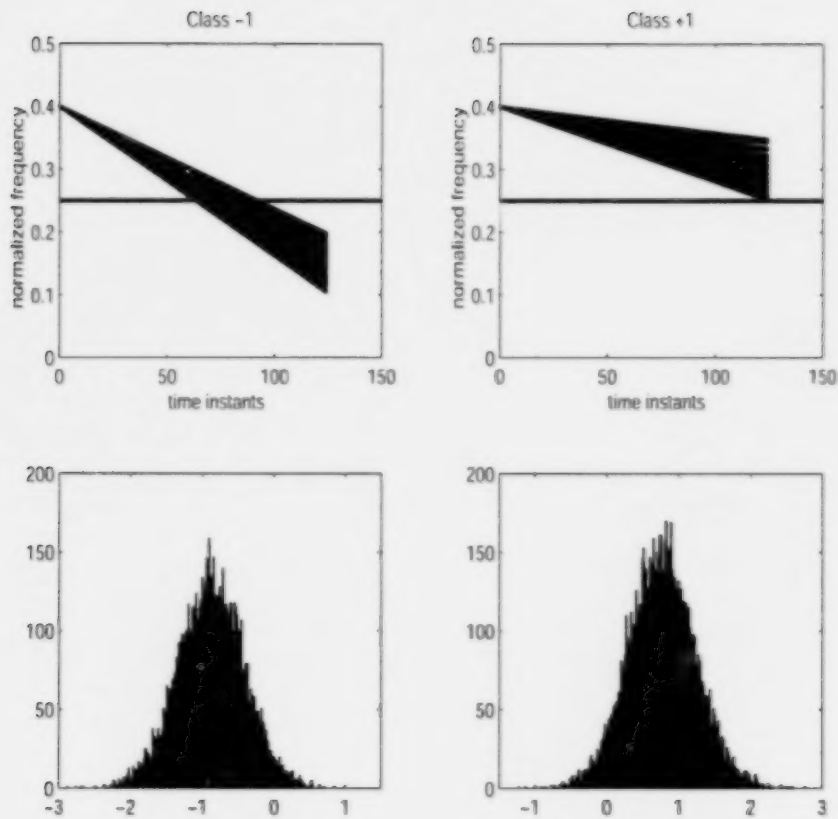


Figure 2: The examples of the binary classification of two chirps. An average error rate was 3.8%. The upper two panels show the chirp slopes distributed randomly for the classes -1 (the left panel) and 1 (the right panel). The two lower panels show histograms of estimated label values for the classes -1 (the left panel) and 1 (the right panel)

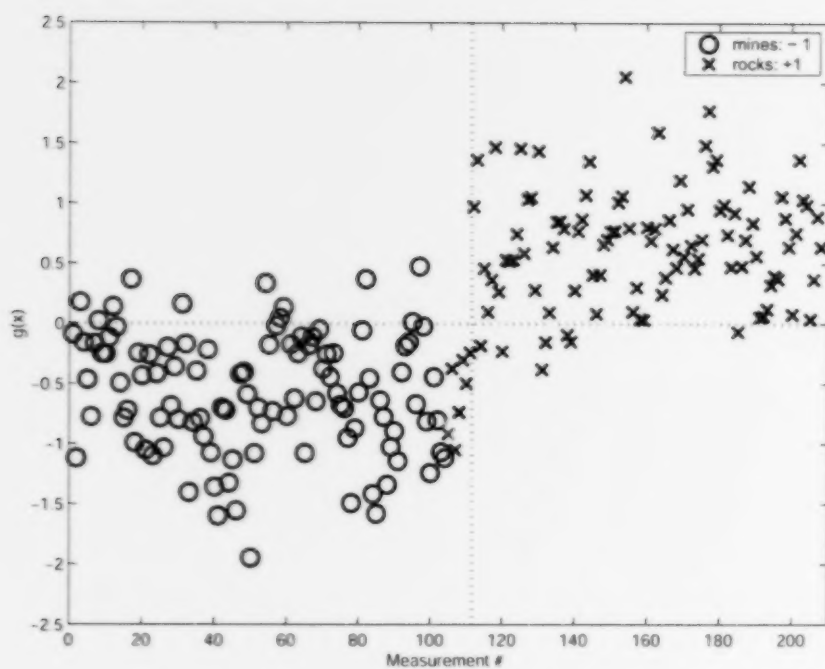


Figure 3: Linear separability of cylinder-like rocks vs metallic cylinders. Training data error rate was 9%

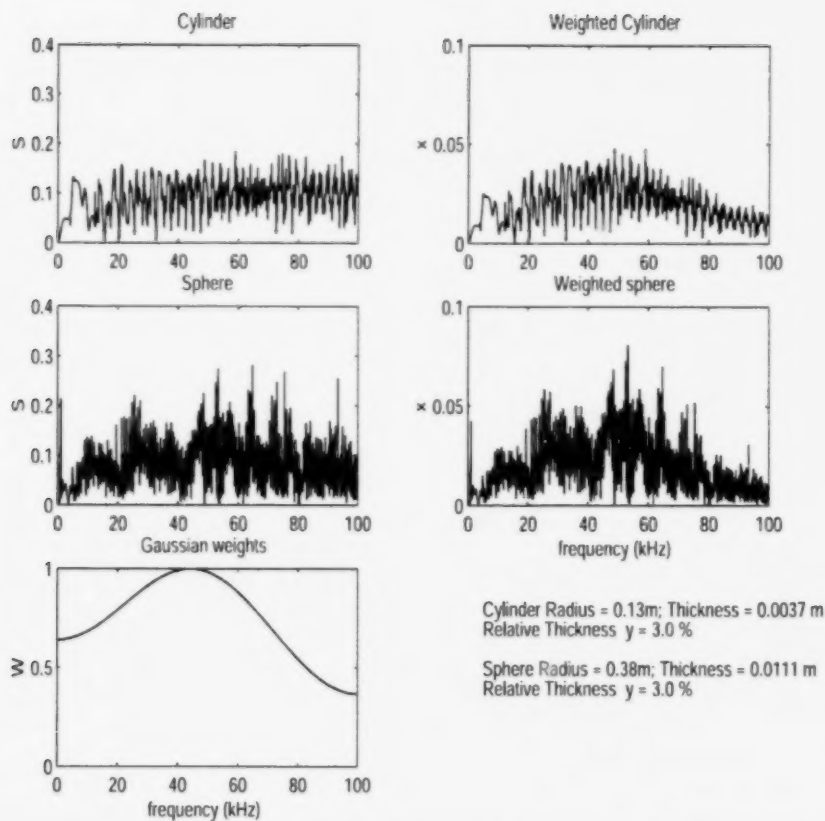


Figure 4: Examples of spectra $|s|$ (two upper left panels) and weighted spectra $|x|$ (the panels on the right) for a sphere and a cylinder. The lower left panel shows the Gaussian weight coefficients $|w|$ that are applied to the spectra of cylinder and sphere

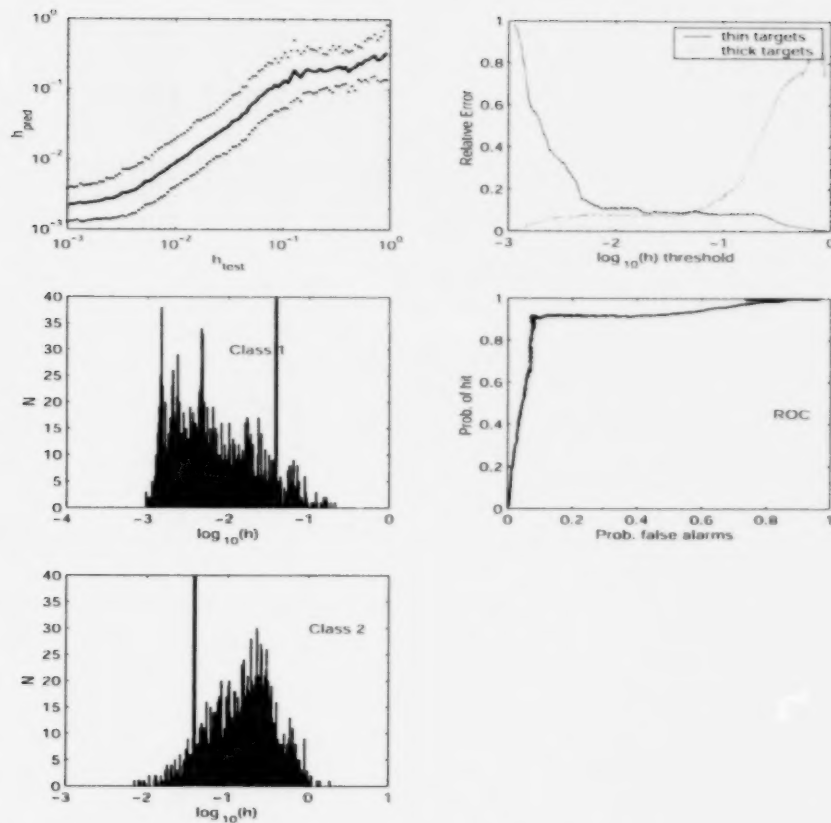


Figure 5: Kernel ridge regression based calculation of the relative thickness of shell: the upper left panel - predicted $\pm$ standard deviation (ordinate) vs actual (abscissa) values, the upper right panel - classification distribution error of thick (green) and thin (blue) targets as a function of threshold of relative thickness; the middle left and the lower left - a histogram of calculated thicknesses divided into two classes using a threshold shown as a vertical red line; the middle right panel - ROC curve as estimated from predicted relative thickness shown in the upper left panel

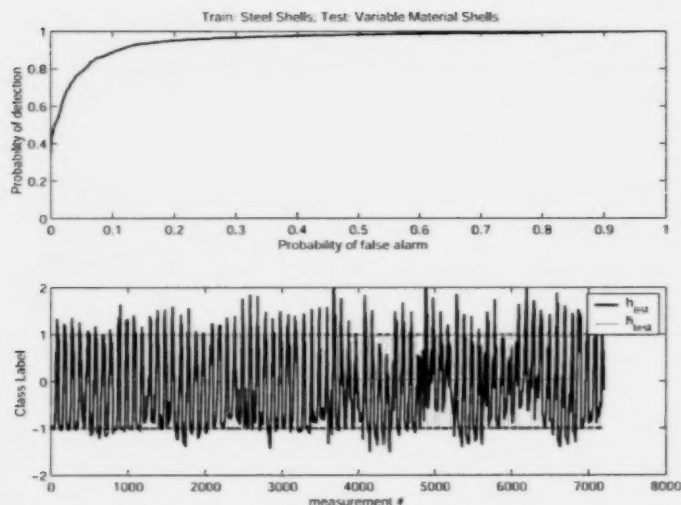


Figure 6: The results of classification of thin vs. thick (including solid) targets; The training data included steel shells and a test was performed on rest of the data (see Table 2, Experiment 4). The upper panel - ROC curve, the lower panel - a distribution of the estimated (blue) and the test labels (green) as a function of measurement number

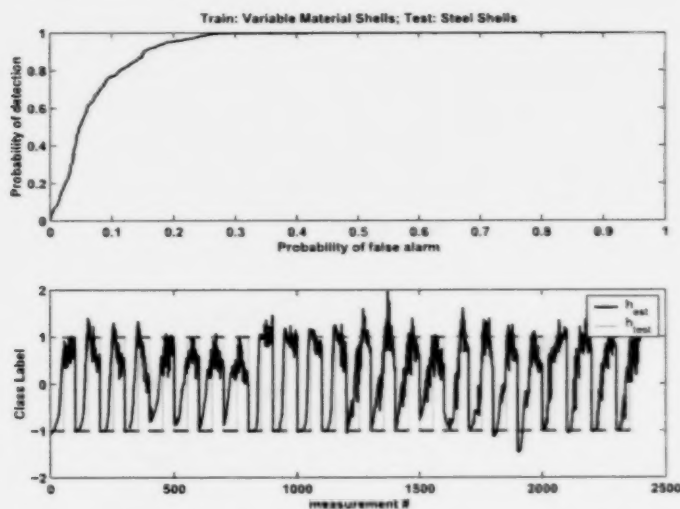


Figure 7: The same as in Figure 6 with the difference that the training data included shells of aluminium, limestone, and basalt; a test was performed on steel shells (Table 2, Experiment 5)

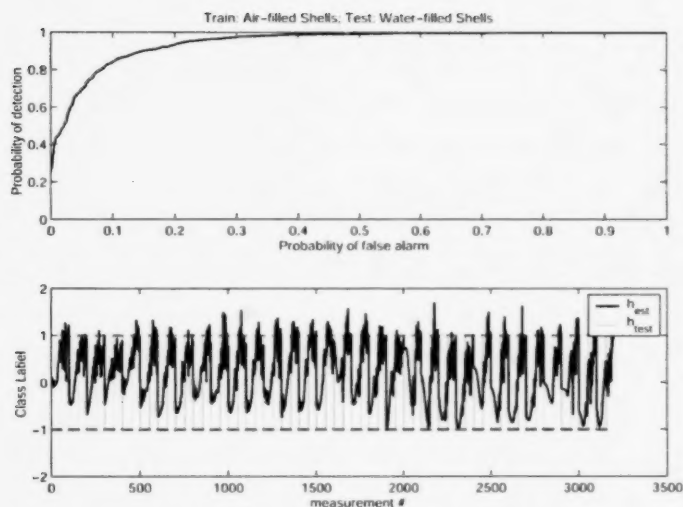


Figure 8: The same as in Figure 6 with the difference that the training data included air-filled shells; a test was performed on water-filled shells (Table 2, Experiment 2)

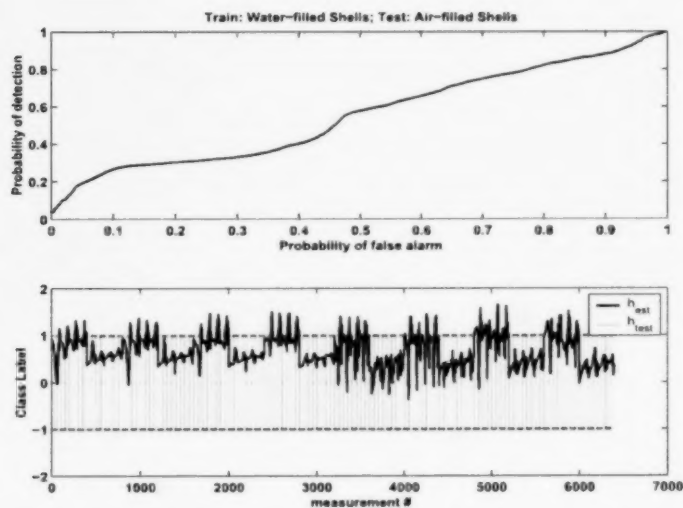


Figure 9: The same as in Figure 6 with the difference that the training data included water-filled shells, a test was performed on air-filled shells (Table 2, Experiment 3)

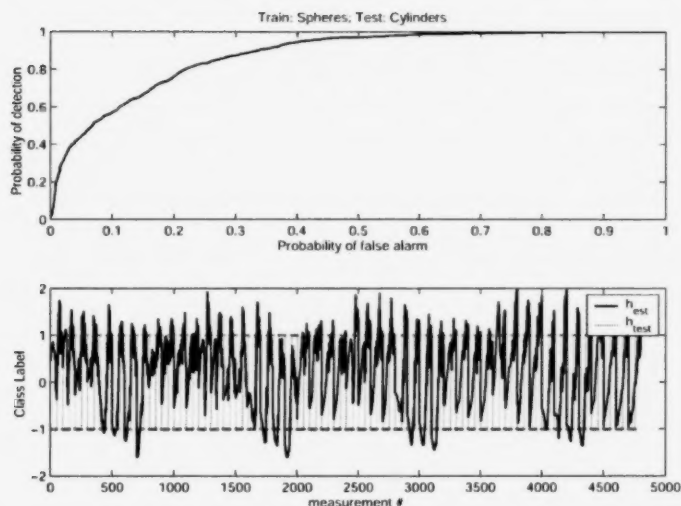


Figure 10: The same as in Figure 6 with the difference that the training data included spheres, and a test was performed on cylinders (Table 2, Experiment 8)

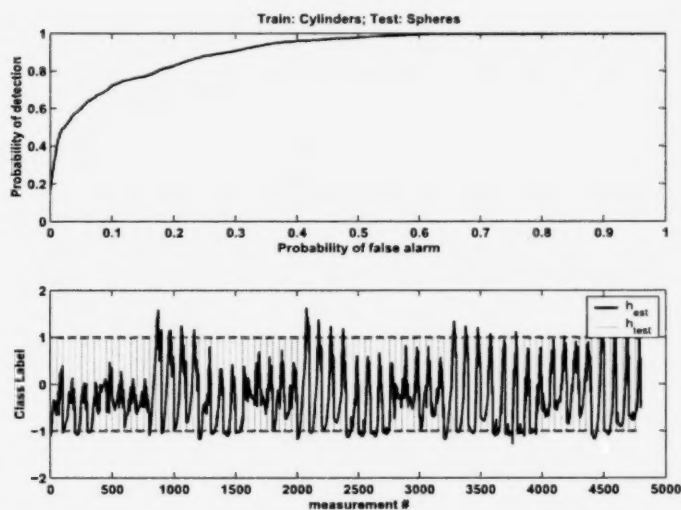


Figure 11: The same as in Figure 6 with the difference that training data included cylinders, a test was performed on spheres (Table 2, Experiment 9)

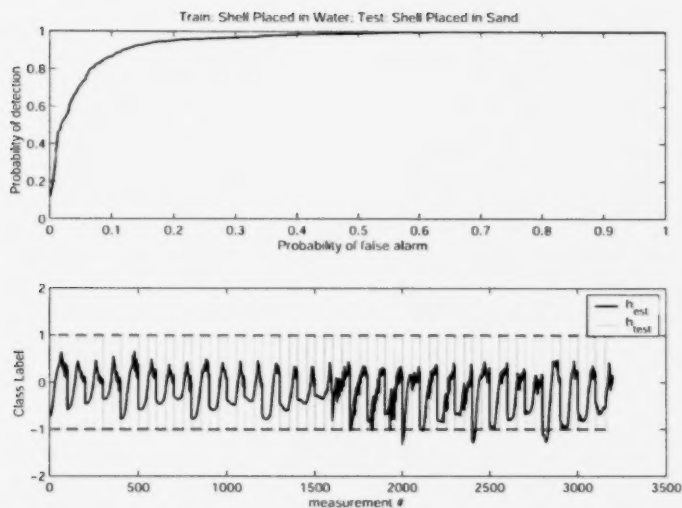


Figure 12: The same as in Figure 6 with the difference that the training data included shells placed in water, and a test was performed on shells placed in sand (Table 2, Experiment 6)

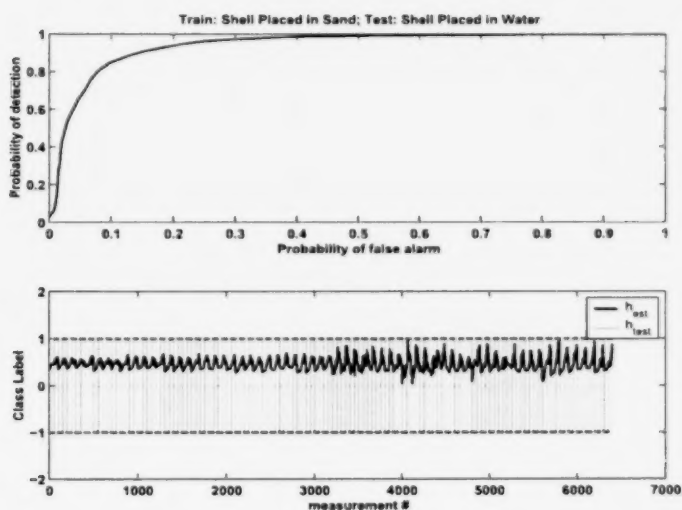


Figure 13: The same as in Figure 6 with the difference that the training data included shells placed in sand, and a test was performed on shells placed in water (Table 2, Experiment 7)

9 Discussion and Conclusions

In this paper we have shown that ridge regression and its kernelized version kernel ridge regression can be applied to a wide range of problems related to the classification of acoustic signatures. We carried out Baseline Classification analysis using the data vectors with a dimension as high as 2000 without feature extraction. Classification results presented in Table 2, show that the overall classification accuracy of the kernel regression classifier when using a random selection of the training and test data varied from 92% (Experiment 1) to 87% (Experiment 10). However, as expected, the classification accuracy changed significantly when some of the types of acoustical signatures were left out of the training data. The classification results were practically insensitive only to shell material. An unexpected result was the asymmetry of the classification results relative to acoustic signatures organized pair-wise by shell filling and the surrounding environment of the shells.

An interesting extension of the above outlined problem is that if one has trained a classifier using the acoustical signatures of sphere and cylinder mine shapes, how accurately will this classifier perform with new previously unseen shapes?

Overall, the results of this study are encouraging. Accurate classification results were obtained. With the inclusion of certain mine and environmental conditions in the training set, a classifier capable of classifying a new mine type was possible. In the future, we hope to test the methods of this report with experimental data.

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(U) We investigate the problem of the detection of mines and the sensitivity of a binary classifier to mine types using a broadband signal incident upon an elastic object. In the course of the sensitivity analysis a realistic situation is simulated when a binary classifier that is optimal for a part of collected- or modeled data turns out to be sub optimal for new, previously unseen data. In general, such a problem corresponds to a generalization problem when for the purpose of classification analysis, the data is set is divided into three parts: training data, test data used for classifiers' fine tuning via cross-validation, and test data not used in the cross-validation. However, in addition to such division, we ensure that one or more types of mines' acoustical signatures are left out of training data, as well as out of test data used for cross-validation purposes. We call such approach a Baseline Classification. To create a data set of mine-like and non mine-like objects that includes the required diversity of mine types, we use analytical models for the elastic shelled spheres and for infinite elastic shelled cylinders. We use a total of 9600 spectra. The spectra can be divided according to their shape, shell material, filling, relative thickness, and surrounding environment into eight types of mines and nonmines. Boundary between mines and non-mines is defined by the relative thickness of shells and it is found that a threshold of 3.5% is optimal. The shells thinner or equal than 3.5% were defined as mines, whereas the rest of shells were defined as non-mines. Overall classification error rate varied from 8 to 23%. As expected, classification accuracy changed significantly with respect to the classes of objects in training set, indicating the cases when the classifier could fail.

(U) Les caractéristiques temporelles (ou de fréquence ou de temps-fréquence) du signal rétrodiffusé sont examinées lors de l'analyse de classification de signaux sonar large bande. Nous espérons que la réponse structurelle-élastique produite par les mines sera sensiblement différente de celle produite par les objets naturels, comme les roches. Le cas échéant, cette réponse fournirait des renseignements utiles permettant de distinguer les mines du clutter.

Une telle approche peut être considérée comme complémentaire à l'analyse d'image acoustique spatiale normalement utilisée avec un sonar haute fréquence bande étroite à balayage latéral.

Nous avons analysé une situation relativement commune où l'on a une connaissance très générale des différents types de mines, mais pas une connaissance détaillée sur leur signature acoustique large bande respective. Dans une telle situation, il ne serait guère surprenant qu'un système de classification formé à l'aide d'un ensemble limité de signatures acoustiques ne soit pas à la hauteur face à un nouveau type de mine. Nous avons analysé le problème de détection/classification des mines en utilisant un signal large bande. En particulier, nous avons examiné la sensibilité du processus de classification par rapport aux types de mines inclus dans l'ensemble d'apprentissage.

Pour obtenir un ensemble de données sur les objets qui ressemblent à des mines et ceux qui ne leur ressemblent pas, qui tient compte de la diversité requise quant aux types de mines, nous avons utilisé des modèles analytiques de sphères à coquille élastique et de cylindres infinis à coquille élastique. Nous avons utilisé un total de 9 600 spectres.

Ces spectres peuvent être classifiés en huit types de mines et d'objets autres que des mines, selon leur forme, le matériau de leur coquille, leur contenu, leur épaisseur relative et selon leur milieu. La frontière qui sépare les mines des objets qui n'en sont pas est définie par l'épaisseur relative des coquilles. Il semble que le seuil optimal aux fins de classification est de 3,5 %. Les objets dont l'épaisseur de la coquille est plus mince ou égale à 3,5 % ont été définis comme étant des mines, alors que les autres ont été définis comme ne l'étant pas. La précision globale de classification variait de 77 à 92 %. Nous avons conclu que le fait de ne pas inclure certains types de mines dans l'ensemble d'apprentissage a entraîné l'« échec » du système de classification.

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(U) pattern analysis, classification, wideband sonar signal, mine-like objects

